

Atmos. Meas. Tech. Discuss., referee comment RC1
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Comment on amt-2022-65

Anonymous Referee #1

Referee comment on "Calibrating Networks of Low-Cost Air Quality Sensors" by Priyanka deSouza et al., Atmos. Meas. Tech. Discuss., <https://doi.org/10.5194/amt-2022-65-RC1>, 2022

This is a very timely paper that provides a systematic and deep analysis on the different ways that low cost sensors can be calibrated by collocation with regulatory grade equipment. In particular, it provides useful information on how best calibrate depending on the collocation period possible. The paper uses a variety of calibration models ($n=21$) starting with simple linear corrections, and ending with complex machine learning algorithms, where it is often difficult to know the mechanism of the correction. The calibration models are tested on four different collocation periods. In particular the difference between the C1 and C2 collocation strategies is interesting because it shows that more calibration data is not necessarily helpful if it doesn't capture the variability in the parameters. The hot spot analysis is also interesting, highlighting the need for care when interpreting individual sensors within a network.

Low cost sensors are used in various ways. Sensor networks like the 'love my air' network used as the data set in this paper are used to complement existing regulatory activities, whereas in other contexts low cost sensors are used where regulatory measurements are scant or non-existent. This paper will provide very useful to all users of low cost sensors.

The paper is very robust in its description and should be published, once the following (mostly minor) points are addressed.

In general, the resolution of the figures should be improved.

Abstract and L49 – no need to say 'gold standard reference monitors', 'reference monitors' is sufficient.

L42 estimates vary widely for number of premature deaths due to air pollution, this should be acknowledged, or at least the prefix of 'approximately' should be added by the 6.7M.

L70 'leading to mass overestimation...' should be 'leading to the (regulatory) dry mass overestimation' or similar

L74 need to acknowledge that most of the PM mass concentration is at particle diameters greater than 300 nm.

L96 Köhler not kohler

L119 I would state that R^2 is a misleading indicator rather than might be

L215-216 you would expect averaged data to have less variance.

L240 RH, T, and D are not independent parameters. A discussion of the use of non-independent parameters within the calibration algorithms should be provided.

L302 how do you choose which site to leave out in the LOSO methodology? What potential bias(es) does this introduce into the analysis?

L333 and most other equations. Pet peeve – use proper multiply symbol rather than x in equations.

L351 “as these concentrations account for the greatest differences in health and air pollution avoidance behavior impacts” this statement is unclear. Are you suggesting that 30 $\mu\text{g}/\text{m}^3$ is a cut off for more harmful PM health effects? My understanding is the health effect: concentration curve is reasonably linear over these ranges.

L393 note a p value of 0.05 means that 1/20 results can be to chance. With 21 models and 4 colocation conditions, you might expect some false positives.

L457 model 2 has a lower RMSE than model 16, so doesn't that contradict "more complex models yielded a better performance"

L472 "the nonlinear correction for RH" gave best performance. Doesn't this suggest a model using a physically reasonable model (essentially k-Köhler) works best when extensive colocation data is not possible. See for example Crilley et al. (2020) <https://doi.org/10.5194/amt-13-1181-2020>

L528 does the temperature offset on CS19 make sense with respect to the position of the sensor?